Set classification of military targets

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Abstract

The present study shows by example the potential amount of information available in a set of observations of targets where there are known relations between these targets. Known relations between objects significantly reduces the set of possible explanations behind a set of observations. The application here is classification of military targets. Cost functions and interaction with decision makers extend the feasibility of the present approach meaningfully to treat many observations and possible targets behind these.

1 Multi-object state-estimation

Classification and tracking of military targets are today often made individually for each object. An approach also utilizing observations of other objects can provide better results. Mahler [1997], Kreinovich [1997] and many others elaborate, within the framework of random sets, on classification of many objects based on a variety of data sources. Theory of random sets provides a direct approach to treat a variety of observations of many targets. This work also takes a direct approach to classify a set of objects.

The focus of this work is by example quantitatively to illustrate the potential amount of information available in the whole set of observations of actual targets. This approach utilizes knowledge about relations between possible targets and their time varying parameters using computer based tools. The present study in general demonstrates the idea of searching through the set of possible explanations (state space) for a given set of observations for the purpose of object tracking and classification.

This work consists of two main parts. The first part illustrates the potential of a full search through a small state space (sections 2, 3 and 4). The second part discusses search in state spaces which are too large to search throughout (section 5).

2 Limited example of information extraction from a set of observations

Appendix A gives an example where a restricted and known set $\mathbf{T} = \{a, b, c, d\}$ of military targets are confined within an area. An observation (or report) $O = a$ means that an observer believes he has observed a (instead of b, c or d) at a given location and time. Let X denote the true origin of the observation O. If $X = a$ then the observation $O = a$ is correct. Otherwise it is false.

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Assume, for simplicity, that each observation has a given uncertainty as follows: A single observation is, in our example, correct with 58 percent probability and the probability to give the report b, c or d is each 14 percent (in total 100 percent). So with standard probabilistic notation, $P(O = a|X = a) = 0.58$ and $P(O = b|X = a) = 0.14$ etc. We assume symmetry with respect to the objects, so $P(O = b|X = b) = 0.58$ and $P(O = a|X = b) = 0.14$ etc. Equation 1 summarizes this information where $x, y \in \mathbf{T}$ and $1 \leq i \leq 4$.

$$P(O_i = x|X_i = y) = \begin{cases} 0.58 & \text{if } x = y \\ 0.14 & \text{otherwise} \end{cases} \tag{1}$$

Given the observations O_1, O_2, O_3 and O_4 with real origin X_1, X_2, X_3 and X_4 respectively. Assume that each set of possible values for X_i (i.e. each *state*) has the same initial probability.

Assume we want to estimate/guess what is the real origin X_1 behind the observation $O_1 = a$. The Bayes rule provides the probability that the real target X_i is a:

$$P(X_i = a|O_i = a) = \frac{P(O_i = a|X_i = a)P(X_i = a)}{P(O_i = a)} \tag{2}$$

where $P(O_i = a) = \sum_{s\in\mathbf{T}} P(O_i = a|X_i = s)P(X_i = s) = 0.58 \cdot 0.25 + 3 \cdot 0.14 \cdot 0.25 = 0.25$. This gives $P(X_i = a|O_i = a) = 0.58$. The probability for $X_i = b$ similarly is:

$$P(X_i = b|O = a) = \frac{P(O_i = a|X_i = b)P(X_i = b)}{P(O_i = a)} \tag{3}$$

which has numerical value 0.14. Each estimate above only depends on one single observation.

If the observations are related, the observations O_2, O_3 and O_4 contain information about X_1. I.e. $P(X_1|O_1 = a, O_2, O_3, O_4)$ is in general different from $P(X_1|O_1 = a)$. We may, for example, be sure that all observations have different objects as origin. This can be the case if the observations for example are simultaneous or the objects are geographically far from each other. The real targets (objects) are in this case all different (provided reliable position estimates for the observations). Spatial location is just one special example of a temporal parameter for an object, so this situation is much more general than for simultaneous observations of geographically distributed targets or where the targets cannot move quickly enough to be observed several times. It can often be easy to find out that two objects, X_1 and X_2, are different even if it is hard exactly to classify the objects. For example, one may easily see that there are two different people on two different unclear photos. However, it is in general much harder to identify the people more exactly. One may only observe that one person is higher than the other or have different clothes the same afternoon. One may have a cellular phone while the other has not etc.

One may in general assume a known (general) relation $\prec$ on the set of possible targets and that this is observable. See the illustration of Figure 1. The actual relations may be static (given for a set of objects) or it can be situation dependent. The relations must in all cases, to be utilized, be part of (or given by) the set of observations.

Assume, for example, that for any possible target X_i and X_j we know if $X_i \prec X_j$ is true or not. $\prec$ may simply mean 'is larger/higher/longer than', 'is different from', 'in front of', 'earlier than', 'faster than' or it can be based on more complex geometric aspect ratios, properties of radar return, emittance etc. $X_i \prec X_j$ may also mean for example that 'X_i wears glasses while X_j does not' from which one can derive that $X_i \neq X_j$.

Assume one is able to observe if the relation $X_i \prec X_j$ is true or not for any target X_i and X_j even if one do not know the exact value of X_i and X_j. We show below that this can include significant information for classification of targets.

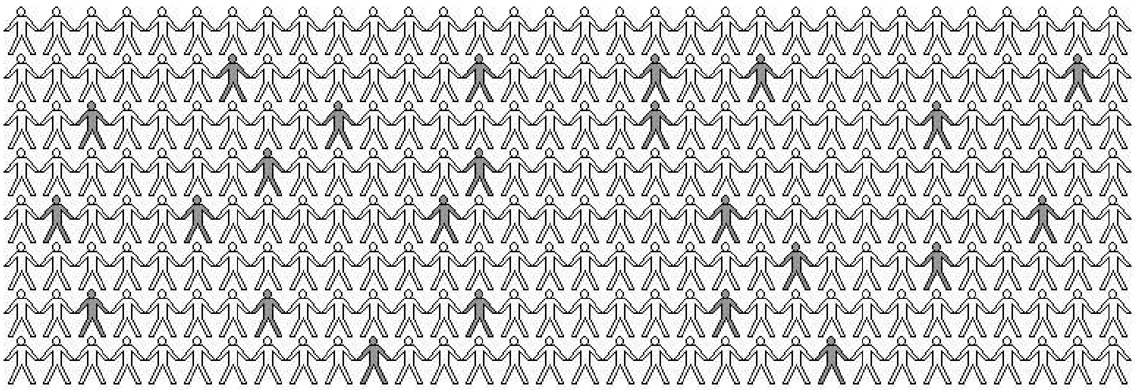

Figure 1: Known relations between objects significantly restricts the number of candidate explanations (sets of classifications) behind a set of observations. Here each person illustrates an explanation for a given set of observations. If there are no restrictions, then four possible objects and four observations gives $4^4 = 256$ possible explanations. If any two observations come from two different targets (for example spatially distributed simultaneous observations), then there are only $4! = 24$ possible candidate explanations. This gives a ratio of 0.094. This ratio decreases fast with increased number of possible targets/observations.

If we assume all objects are different, and denote this 'relation' by $\mathcal{R}$, we get by simple numerical simulations (see appendix B) that

$$P(X_1 = a | O_1 = a, O_2 = b, O_3 = c, O_4 = d, \mathcal{R}) = 0.80 \tag{4}$$

which is considerably different from $P(X_1 = a | O_1 = a) = 0.58$. If we have ground truth data for an object, for example $X_2 = b$, we get even more certainty:

$$P(X_1 = a | O_1 = a, O_2 = b, O_3 = c, O_4 = d, X_2 = b, \mathcal{R}) = 0.88 \tag{5}$$

And if we also have the ground truth data $X_3 = c$ we get:

$$P(X_1 = a | O_1 = a, O_2 = b, O_3 = c, O_4 = d, X_2 = b, X_3 = c, \mathcal{R}) = 0.94 \tag{6}$$

If the set of observations are not consistent, this will increase the uncertainty. Assume we know that all observed targets are different, but two observations give the same independent classification such as for example $O_3 = O_4 = c$. We then get that

$$P(X_1 = a | O_1 = a, O_2 = b, O_3 = c, O_4 = c, \mathcal{R}) = 0.67 \tag{7}$$

The intuitive explanation here is that the inconsistency (i.e. that $O_3 = O_4$) tells that at least one of the observations O_3 and O_4 is wrong and therefore a may be hidden behind one of these observations.

If a is given by the observations to be two places at the same time, this further increases the confusion:

$$P(X_1 = a | O_1 = a, O_2 = b, O_3 = c, O_4 = a, \mathcal{R}) = 0.50 \tag{8}$$

And if a is given to be 3 places at the same time, the uncertainty even increase:

$$P(X_1 = a | O_1 = a, O_2 = b, O_3 = a, O_4 = a, \mathcal{R}) = 0.33 \tag{9}$$

If a is initially classified to be at 4 places at the same time, then $P(X_1 = a|O_1 = a, O_2 = a, O_3 = a, O_4 = a, \mathcal{R}) = 0.25$. These estimates conform to common sense since inconsistent observations have to include errors.

These estimated probabilities can be used in a cost assessment as shown in appendix A.2. The cost assessment might be of help to a decision maker making a decision of how to react to these observations.

3 Generalizations of limited example

3.1 Increased and reduced number of observations

The limited example of Section 2 assumes the number of observations to be the same as the number of targets. This section shows a way to generalize this restriction allowing the number of targets to be different from the number of observations. The purpose of this generalization is to show that the amount of available information - the number of observations - is important with respect to probability estimates like the ones in equations 4 - 9.

Assume $\mathcal{R}_1$ represents the relation that the objects generating the observations $O_1, \ldots, O_4$ are different (as in Section 2), while the objects behind O_1 and O_5 are the same (i.e. $X_1 = X_5$). A similar simple numerical simulation as in Section 2, provides the following estimate:

$$P(X_1 = a|O_1 = a, O_2 = b, O_3 = c, O_4 = d, O_5 = a, \mathcal{R}_1) = 0.95 \tag{10}$$

This shows that the additional observation O_5, and the known relationship that $X_1 = X_5$, gives an improved confidence in the classification of X_1 (cf Equation 4).

Reduction of the set of observations also has effect on the quality of classification in the present approach. Let $\mathcal{R}_2$ denote that the objects generating the observations O_1, O_2, O_3 are different. We then get that

$$P(X_1 = a|O_1 = a, O_2 = b, O_3 = c, \mathcal{R}_2) = 0.69 \tag{11}$$

which is a considerable reduction of confidence in the classification of X_1 (cf Equation 4).

3.2 Classifying a set of not precisely known targets within a restricted area

This section illustrates a generalization of the classification problem of Section 2 which assumed a small number of known targets within a restricted area. Assume now that the actual four targets are members of a set $\Omega = \{a_1, a_2, \ldots, a_{11}\}$ of 11 classifications and that the quality of observations are the same as in the above examples. Equation 12 defines (similar to Equation 1) the quality of the observations:

$$P(O_i = x|X_i = y) = \begin{cases} 0.30 & \text{if } x = y \\ 0.07 & \text{otherwise} \end{cases} \tag{12}$$

where both x and y are an element of Ω and $1 \leq i \leq 4$. This conforms to the quality of observations assumed in Section 2 (Equation 1).

If there are no known relations between the targets, then the probability of $X_1 = a_1$ given the observation $O_1 = a_1$ is $P(X_1 = a_1|O_1 = a_1) = 0.30$ (cf Equation 2).

Assume, as above, four observations $O_i = a_i$, $i = 1, 2, 3, 4$ and that all objects are different ($\mathcal{R}$). We get in this case that (still via simple simulations):

$$P(X_1 = a_1|O_i = a_i, \mathcal{R}) = 0.32 \qquad i = 1, 2, 3, 4 \tag{13}$$

where $\mathcal{R}$ as above denotes that all objects $X_1,\ldots,X_4$ are different. As opposed to in the classification problem of section 2 (see equation 4), the information ($\mathcal{R}$) that the targets are different do not significantly decrease the uncertainty of classification (note from above that $P(X_1 = a_1|O_1 = a_1) = 0.30$).

Assume now, as an illustration, that the relative sizes of the 4 targets constitutes a strong linear relation $\prec$ on the set Ω of 4 targets. It might e.g. be known that object 1 is smaller than object 2, which is smaller than object 3 etc. (i.e. as if the elements of Ω were logically organized along a line).

This means, mathematically, that for any two different objects X, Y in Ω, either $X \prec Y$ or $Y \prec X$. It also means that $X \prec Y$ and $Y \prec Z$ gives that $X \prec Z$ (and it is never true that $X \prec X$). If we know, for example, that X_1 is 'less than' another observed object X_2 (i.e. $X_1 \prec X_2$), then we get:

$$P(X_1 = a_1|X_1 \prec X_2) = 0.56 \tag{14}$$

Similarly we have that

$$P(X_1 = a_1|X_1 \prec X_2 \prec X_3) = 0.76 \tag{15}$$

and if all the four observed objects are strongly linearly related:

$$P(X_1 = a_1|X_1 \prec X_2 \prec X_3 \prec X_4) = 0.90 \tag{16}$$

4 Initial probabilities

The above statistical approach assumes a homogeneous distribution of the initial probabilities over the set of possible states. This is a natural choice when there is no information giving preference to special alternatives. The use of the relation $\mathcal{R}$ above can be looked at as defining an initial probability where the states not conforming to the relation has probability zero (and the other states each having the same initial probability). A certain relation, in other words, restricts the search space or concentrates the probability to the subspace conforming to the relation. Other types of initial distributions can have similar effects on the classifications similar to those above.

5 Treatment of many objects

5.1 Restricting the search

The examples above assumes, for a large number of objects, heavy computing and the method is therefore not directly practical for large problems. A main challenge is therefore meaningfully to search through only a smaller part of the state space or to search through it in a cost effective manner and eventually to stop processing when sufficient results are obtained. An algorithm can use knowledge about physical restrictions and information from intelligence in order to reduce the search space. Situation and threat assessments can also provide information for restricting the search space for finding sufficient information for actual decisions. This approach for efficient search requires flexible user interactions.

5.2 Ordered and restricted search

Assume a set $\mathbf{o} = \{O_1, O_2, \ldots, O_M\}$ of M independent observations of singular members of a large set $\{a_1, a_2 \ldots, a_N\}$ of N targets within a restricted area (say $N \simeq 20$). X_i denotes the true value behind the observation O_i and an observer with incomplete information about it, may treat X_i as a random variable.

Assume that each state $\mathbf{x} = (X_1, \ldots, X_M)$, has an associated "interest to know". I.e. there is a payoff (or saved cost) associated with information about the values of X_i. One may therefore want to estimate the probability distribution for x or at least obtain partly knowledge about its probability distribution.

An efficient search after estimates of the probability of "interesting" states, can utilize an initial probability distribution on the state space. The search can in this way first look through parts of the search space with the highest expected payoff. Let $\mathbf{A}$ and $\mathbf{B}$ be two different parts of the search space. Given that $I(\mathbf{x} \in \mathbf{A})$ and $I(\mathbf{x} \in \mathbf{B})$ are the payoffs to know if $\mathbf{x} \in \mathbf{A}$ and $\mathbf{x} \in \mathbf{B}$, respectively, and that $\mathbf{x} \in \mathbf{A}$ and $\mathbf{x} \in \mathbf{B}$ similarly has initial (unconditional) probabilities $P(\mathbf{x} \in \mathbf{A})$ and $P(\mathbf{x} \in \mathbf{B})$. If a decision component must make a priority between calculating $P(\mathbf{x} \in \mathbf{A}|\mathbf{o})$ or $P(\mathbf{x} \in \mathbf{B}|\mathbf{o})$ (for example within a given time), then estimating $P(\mathbf{x} \in \mathbf{A}|\mathbf{o})$ would be a natural choice if the expected payoff $C(\mathbf{A}) = I(\mathbf{x} \in \mathbf{A}) \cdot P(\mathbf{x} \in \mathbf{A})$ is significantly larger than $C(\mathbf{B}) = I(\mathbf{x} \in \mathbf{B}) \cdot P(\mathbf{x} \in \mathbf{B})$. If the payoff from estimates for $\mathbf{x} \in \mathbf{B}$ is expected to be much larger than the cost of waiting for the estimates, then a natural choice would be to wait for estimates for $\mathbf{x} \in \mathbf{B}$. If $I(\mathbf{x} \in A) = 0$ or $P(\mathbf{x} \in \mathbf{A}) = 0$, then the part A may not be interesting to search through.

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Appendix

A Scenario

A.1 Intelligence operation within a restricted area

The following scenario illustrates the use of the present approach to help establishing a situation picture. An unknown (potentially hostile) group of four boats (a, b, c, d) is observed entering a Norwegian fjord. Intelligence and general situation assessment results in that a team is set up with the mission to monitor the boats. The monitoring is to be conducted in a discrete/hidden manner to prevent revealing the level of monitoring, hence helicopters, radars etc. cannot be used. Revealing, for an enemy, the level of monitoring and response patterns is regarded to increase to vulnerability in the given situation and it will also increase the need for costly change in security related investments.

There are several hypotheses for why the boats have entered the fjord:

H1: They are regular tourist boats.

H2: At least one boat (boat a) is testing our intelligence, level of alert and response patterns.

H3: The boat a is for sabotaging a power plant in the fjord.

The intelligence team is assumed to report if the power plant is at risk (early enough to protect this possible target).

The outlet of the fjord is well observed, meaning that it is known how many boats have entered the fjord and that any boats coming into the fjord will be spotted. The boats can be distinguished from each other via different characteristics (different sizes, different types of boats, etc.). Further, one can easily find out if two observations of boats are for different boats or not. Each observation is given a confidence as in Equation 1. The mission for the team is (in a hidden way) to monitor all four boats as well as possible while evaluating the risk for sabotage.

A.2 Cost Assessment

The power plant is assumed to have a (relative) value of $I_{\text{power plant}} = 100$. The cost of revealing the intelligence/monitoring level is assumed to be less than the limit $S = 5$. Only one of the boats (boat a) is assumed to be large enough to be equipped for attacking the power plant. If the boat a enters a "red zone" close to the power plant, it is given a probability p_{attack} to attack the power plant. Assume, according to Section 2 above, the observations $\mathbf{o} = \{O_1 = a, O_2 = b, O_3 = c, O_4 = d\}$. So if a boat X_1 is observed within the "red zone", and the classification only includes use of observation O_1, the expected cost of the choice of not taking action would be:

$$C_{\text{no action}} = p_{\text{attack}} \cdot P(X_1 = a|O_1 = a) \cdot I_{\text{power plant}} \tag{17}$$

For $p_{\text{attack}} = 0.10$, $P(X_1 = a|O_1 = a) = 0.58$, and $I_{\text{power plant}} = 100$ this gives $C = 5.8$ which is close to the cost of revealing the intelligence. Hence the individual classification estimate $P(X_1 = a|O_1 = a) = 0.58$ does not provide a clear conclusion (decision). The similar expected cost, taking into account the whole set of observations, would be

$$\begin{aligned} C'_{\text{no action}} = p_{\text{attack}} \cdot \\ P(X_1 = a|\mathbf{o}, \mathcal{R}) \cdot I_{\text{power plant}} \end{aligned} \tag{18}$$

giving, according to Equation 4, $C = 8$. If there were ground truth data for X_2 and X_3 (cf Equation 6), then we would get $C = 9.4$.

Assume (still) that boat a is known to be hostile. If there is no significant cost associated with checking up a regular tourist boat, then the expected cost of taking action similarly would be less than

$$C_{\text{action}} = S \cdot P(X_1 = a|O_1 = a) = 2.9 \tag{19}$$

and

$$C'_{\text{action}} = S \cdot P(X_1 = a|\mathbf{o}, \mathcal{R}) = 4.0. \tag{20}$$

If there were a high cost associated with the possibility that X_1 was a regular tourist boat, and b, c and d were confirmed to be tourist boats, then there would be an additional cost proportional to $P(X_1 \neq a|O_1 = a) = 0.42$, $P(X_1 \neq a|o, \mathcal{R}) = 0.20$ or alternatively $P(X_1 \neq a|o, X_2 = b, X_3 = c, \mathcal{R}) = 0.06$. These alternative estimates for the probability for $X_1 = a$ could in this case give large differences in cost estimates.

B Numerical simulation algorithm

This section describes the simulations providing the estimates of classification probabilities used in this paper. The following points outline the algorithm:

1. A set of all possible realities explaining the original observation vector (explanations) is generated. The size of this set depends on the size of the original observation vector (the number

of observations), the number of possible classifications of the objects generating the original observation vector, and on the possible restrictions. E.g.: with an original observation vector of 5 single observations, 4 possible classifications, and no restrictions, the set of explanations is a matrix of size $5^4 \times 5$. With an original observation vector of size 4, 4 possible classifications and the restriction that the 4 items in the observation vector originate from different objects, the size of the matrix will be $4! \times 4$.

2. For each explanation, 1000 observation vectors of the same size as the original observation vector are generated. Each of these observation vectors are generated randomly based on the sensor likelihood, i.e.: for each entry in the explanation, a random number is drawn and compared to the likelihood. The outcome of this comparison decides what observation is generated by this particular explanation.

3. The fraction of these 1000 observation vectors equal to the original observation vector, represents how well the possible explanation explains the original observation.

This part of the algorithm is repeated N times, and the mean fraction for each possible explanation is recorded as the final result.

Consider, as an example, an original observation vector $\mathbf{oov} = \begin{bmatrix} a & b & c \end{bmatrix}$, where the possible classifications are a, b and c. With the restriction that the 3 items in **oov** originate from different objects, the matrix of explanations will look like this:

$$\begin{bmatrix} a & b & c \\ a & c & b \\ b & a & c \\ b & c & a \\ c & a & b \\ c & b & a \end{bmatrix}$$

The algorithm then could produce the following result:

possible explanation	result	fraction
$[\ a\ b\ c\ ]$	750	0.75
$[\ a\ c\ b\ ]$	130	0.13
$[\ b\ a\ c\ ]$	40	0.04
$[\ b\ c\ a\ ]$	20	0.02
$[\ c\ a\ b\ ]$	20	0.02
$[\ c\ b\ a\ ]$	40	0.04

This result gives the estimate

$$\begin{aligned} &P(X_1 = a|O_1 = a, O_2 = b, O_3 = c, \mathcal{R}_3) = \\ &\quad P(X_1 = a, X_2 = b, X_3 = c|O_1 = a, O_2 = b, O_3 = c, \mathcal{R}_3) + \\ &\quad P(X_1 = a, X_2 = c, X_3 = b|O_1 = a, O_2 = b, O_3 = c, \mathcal{R}_3) = \\ &\quad 0.75 + 0.13 = 0.88 \end{aligned}$$

where $\mathcal{R}_3$ represents the restriction that X_1, X_2 and X_3 are different.

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Set classification of military targets

Elaboration of possible consistent explanations for a set of observations by using available information.

Issues for this talk:

- *Show examples of how classification can be affected by intelligence reports from a situation.*
- *To explore potentials for better formalized use of available information within classification.*
- *Show generalizations of simple model study.*
- *Illustrate the potential amount of information available in a set of observations of targets where there are known relations between them.*

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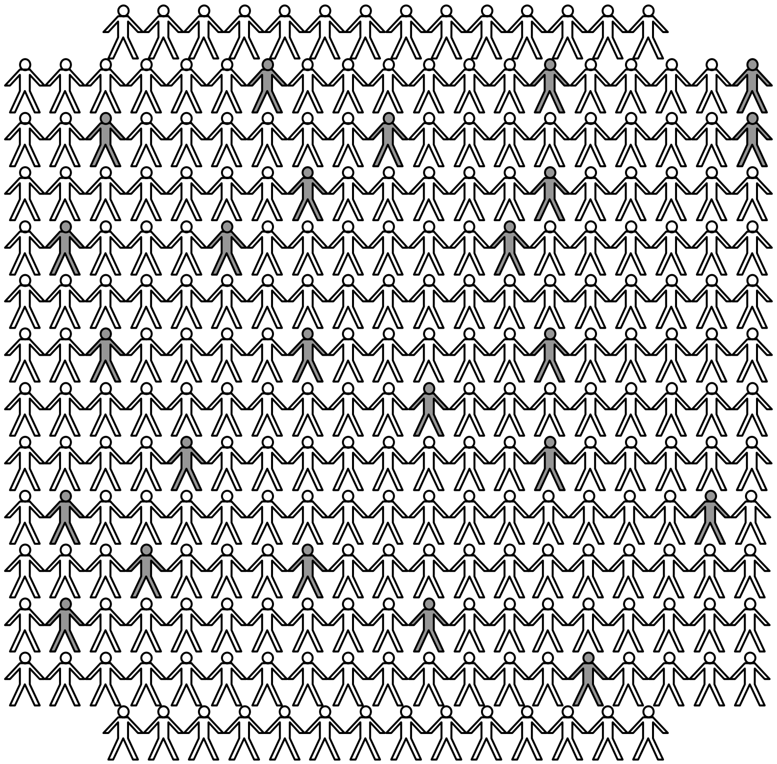
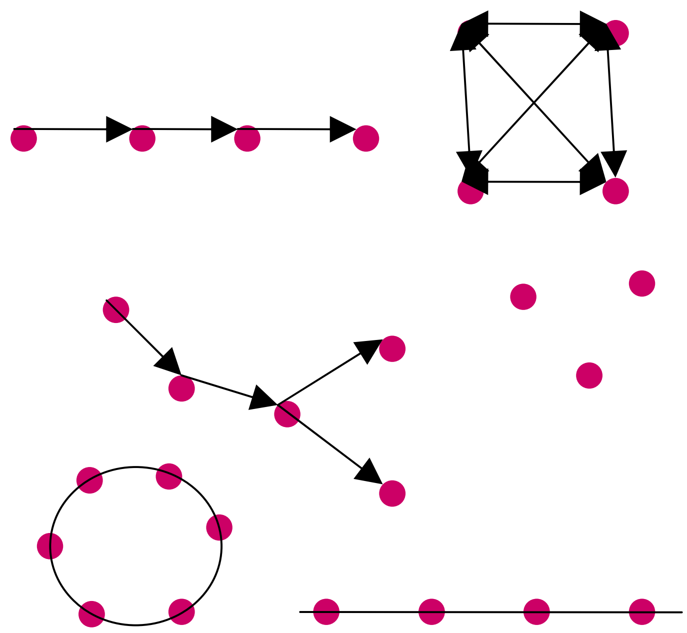
The set of possible explanations is large - hence a need for reductions



- *Known relations between objects (and other facts) restrict the number of possible explanations for a set of observations.*
- *Relations between targets (also uncertain relations) can in general affect preferences between explanations (so a relation may be given with some certainty).*

Examples of relations between targets (useful for classification):



- *Some targets are different from each other.*
- *Some targets are larger, higher, longer than others.*
- *Targets may have different attributes.*
- *Some targets give more radar return than others.*
- *Some targets are in front of others.*

Example

- *Four targets (boats) in a restricted area (Norwegian fjord).*
- *Four observations where observers classify an object from a list of these objects.*
- *Likelihood function: Given an observed object "a", then there is 58 percent probability it is classified as "a" (and 14 percent for the other three).*

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Example continued: Treatment of observations

- *We assume observations O = {O1=a, O2=b, O3=c, O4=d} and targets X = {X1, X2, X3, X4} which we want to classify (i.e. we want to estimate the probability distribution of X1, X2, X3, X4 given available information).*
- *Isolated assessment: P(X1=a|O=a) = 0.58 (where X1 denotes the target for observation O1).*
- *Assuming all four targets different gives: P(X1=a| "all targets different") = 0.8.*
- *If, in addition, X2=b is confirmed, P(X1=a| conditions) = 0.94).*

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Example 2

- 11 objects {a,b,...,k}.

- 4 observations {O1=a,O2=b,O3=c,O4=d}.

- Likelihood function: P(O1=a|X1=a) = 0.30 and P(O1=a|X1=b) = 0.07, P(O2=a|X1=c) = 0.07 etc.

- P(X1 = a | O1=a,O2=b,O3=c,O4=d) = 0.32.

- Assuming the targets can be linearly ordered:
P(X1=a|X1<X2<X3<X4) = 0.90

Treatment of many objects

- *Reduce search space.*
- *Ordered search.*
- *Focus on important/critical information for decisions (for example is P(a | conditions) > x ?*
- *Split up the search space (in independent parts).*
- *Combine ”good aspects” / creative search: evolution.*
- *Threat analysis: Paranoid search.*